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Adaptive Robot-Assisted Telerehabilitation System Using Model Predictive Control and Digital Twin for Personalized Upper Limb Therapy

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Abstract:

Smart rehabilitation systems have revolutionized the delivery of upper limb therapy, with treatments that are more accurate, adaptive, and patient-focused. An advanced rehabilitation system integrating Model Predictive Control (MPC), Digital Twin visualization, and Augmented Reality (AR) interfaces ensures personalized and adaptive therapy. Real-time data are processed by the system with low latency of 10 ms, reducing X, Y, and Z axes trajectory tracking errors. The system changes treatment from 80 units to 79.85 units according to the patient's level of fatigue (0.5) and enhances comfort and rehabilitation results. The Digital Twin module provides an immediate virtual representation of therapy progress, and AR interfaces enable remote monitoring and control. The integration of MPC, AR, and Digital Twin technologies offers an efficient and highly adaptive rehabilitation approach that is well-suited for clinical applications as well as for at-home therapy. The results indicate the system had the potential to enhance patient care, refine therapy accuracy, and maximize rehabilitation effectiveness.

Keywords: *Rehabilitation Therapy, Model Predictive Control, Digital Twin, Augmented Reality, Real-Time Adaptation, Upper Limb Recovery*

1.Introduction:

Advancements in the IoT, AI, and robotics are propelling major enhancements in healthcare systems. Health monitoring frameworks empowered by IoT, which include fog computing and wearable devices, provide real-time diagnostic functions and facilitate remote patient monitoring, encompassing individuals such as children and the elderly (Ganesan, n.d.; Grandhi et al., 2025) . Techniques such as Discrete Wavelet Transform (DWT) in ECG analysis improve signal accuracy and facilitate more efficient cardiac monitoring (Sowmya et al., 2024). Through the use of communication technology innovations, IoT is rapidly evolving, with billions of connected devices worldwide. A cluster-based routing strategy for Bluetooth low-energy ad hoc networks improves node discovery and reduces energy consumption by lessening message routing, with RPMA, BLE, and LTE-M being fundamental wireless technologies during this transition (Chauhan, 2023). In the realm of pediatric healthcare, the effectiveness of predictive analytics—and, by extension, patient outcomes—depends on solid data preprocessing and feature extraction(Grandhi, n.d.).With the rise in IoT adoption, it becomes ever more essential to secure these systems—especially to safeguard sensitive health data and uphold trust in healthcare delivery (Samudrala et al., 2023)

Recent studies highlight the increasing necessity for secure and efficient automation in healthcare, logistics, and other fields. Research has examined the difficulties associated with RPA adoption and the crucial role of competent management in guaranteeing successful implementations (Gollavilli et al., 2025; Nippatla et al., 2025). To enhance the diagnosis of CKD, manage uncertainty, and improve prediction accuracy, advanced AI methods such as fuzzy cognitive maps, ANFIS, and LSTM networks have been utilized(Sitaraman, 2022). To guarantee accurate and secure package delivery, robotic delivery systems are integrating biometric and AI-based authentication modules (Basani et al., 2024). Health monitoring frameworks empowered by IoT, which incorporate fog technology and real-time AI models, push the boundaries of predictive healthcare (Kethu et al., 2025) (Deevi, 2020)). The initiatives demonstrate the revolutionary possibilities of merging AI, IoT, and robotic process automation to improve efficiency, precision, and security in various sectors.

Current works have several limitations when it comes to optimizing robotic operations and human-robot interaction. Challenges like inadequate multi-robot planning and communication impede exploration efficiency, whereas traditional emotion recognition methods do not integrate contextual facial information, leading to reduced accuracy (R. L. Gudivaka et al., 2024) .(Palanivel et al., 2024) Current techniques often face challenges with real-time navigation, obstacle avoidance, and environmental mapping under dynamic conditions, lacking robust solutions for adapting to complex scenarios (Sitaraman and Khalid, 2025). Security frameworks for robotic cloud systems are also inadequately integrated, possessing limited ability to analyze complex data patterns and effectively identify attacks (B. R. Gudivaka et al., 2024) . To tackle these gaps, it is necessary to implement new approaches that merge cutting-edge computational paradigms, enhance contextual comprehension, and bolster the adaptability and security of robotic systems.

1.1. Problem Statement:

With the growing need for customized rehabilitation solutions in healthcare, there is a challenge of providing efficient, dynamic, and scalable therapy to patients rehabilitating their upper limbs(Gudivaka, 2024). Traditional rehabilitation techniques fail to include real-time adaptation based on the physical condition of the patient, leading to suboptimal results (Basani, n.d.).

1.2. Objectives:

- Establish a real-time data collection system using IoT sensors to monitor patient movements, joint angles, and muscle activity during upper limb therapy.
- Apply Model Predictive Control (MPC) to optimize robot movements and adjust therapy intensity based on real-time sensor feedback, ensuring personalized treatment.

- Design an Augmented Reality (AR) remote operation interface that allows operators to adjust therapy parameters and monitor patient performance remotely.

2. Literature review:

(Mamidala, n.d.). presented, the scalability and efficiency of RPA in cost accounting and financial accounting systems. Process identification, workflow model creation, development of RPA, and measurement of performance form the part of its systematic methodology. To seamlessly send and receive data, Excel, databases, and APIs are employed by the process to interact with ERP platforms, financial databases, and report creation tools. CKD (chronic kidney disease) is a significant global health threat. In order to attain better patient prognoses, early diagnosis and prediction are necessary. This paper proposes a novel hybrid model that integrates a stochastic fuzzy system with bidirectional long short term memory (Bi-LSTM) to improve CKD prediction in robotic systems using the Internet of Medical Things (IoMT).

Stochastic fuzzy systems handle with uncertainty in health data to facilitate better decision-making on one hand; bi-LSTM is capable of absorbing data trends information coming in both directions since they are created(Alavilli et al., 2024). (Grandhi et al., 2024) presented in a study, which integrates the Internet of Medical Things (IoMT), robot automation, and artificial intelligence (AI). The authors utilized Recurrent Neural Networks (RNN) to detect patterns over time in patient data and Type-2 fuzzy logic to control uncertainties and vagueness. With robotic automation, data processing efficiency was increased, human error was diminished, and productivity was expanded. The technique allowed real-time monitoring and the ability to personalize healthcare interventions for the individual, leading to substantial enrichments in the accuracy and effectiveness of CKD predictions.

(Gudivaka, 2021) imported the Smart Comrade Robot that integrated AI and robotic technologies to strengthen care for elderly citizens. The robot provided daily assistance, health monitoring, fall alert, and emergency notification. The system built use of platforms like IBM Watson Health and Google Cloud AI to provide proactive, personalized care that upgraded the lifestyle of the elderly and lightened the workload for caregivers. (Gudivaka, 2020) indicated a new approach that integrated robotic process automation (RPA) with cloud computing to enhance the utility of social robots, particularly for older people and those with cognitive disabilities. The indicated d system leveraged the processing power of cloud computing to enable responsive user interaction, effective task scheduling, and real-time object and behavior recognition. Critical elements like the Behavior Recognition Engine (BRE), Object Recognition Engine (ORE), and Semantic Localization System (SLS) were upgraded through advanced deep learning models executed in the cloud. This approach improved the robot's reliability and accuracy in task performance, navigation, and user interaction.

(Gudivaka and Infotek, n.d.) investigated methods to enhance IoT and RPA systems through the implementation of PCA, LASSO, and ESSANN. The approach optimized data management, enhanced predictive accuracy, and assisted automating complex procedures by integrating the techniques for preprocessing, feature engineering, and predicting models. (Basani, 2024) presented joint YOLOv3-Mask RCNN model to enhance object localization in IoT-integrated RPA systems. This approach combined the pixel-level segmentation precision of Mask-RCNN with the real-time detection efficiency of YOLOv3, with an aim to improve processing speed as well as localization accuracy. The strategy embedded training, validating, and evaluating on various IoT scenarios, emphasizing improved computational efficacy and higher accuracy in object detection

2. Proposed Methodology

The advanced method for the Adaptive Robot-Assisted Telerehabilitation System assimilates IoT sensors, Model Predictive Control (MPC), and Digital Twin technology to provide an adaptive and personalized upper limb rehabilitation solution. Real-time data is collected from a variety of IoT devices and sensors to observe the patient's movements, joint angles, and muscle activity. This information is poured using Apache Kafka to enable smooth and effective transmission of data to the MPC, which modifies the movements of the robot and therapy intensity based on the patient's progress.

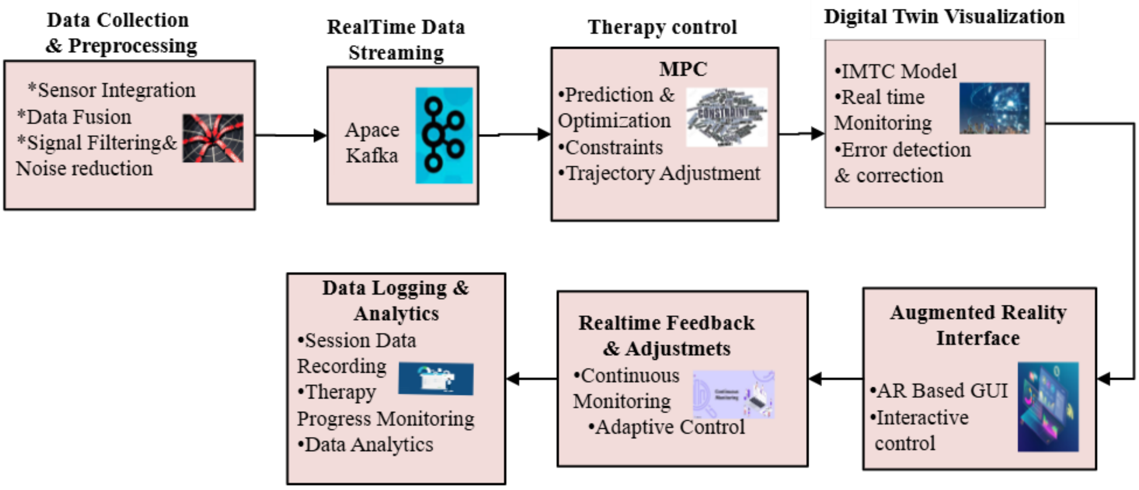

Figure 1: Block diagram of Integrated Digital Twin Control System

meanwhile, the Digital Twin creates a virtual replica of the robot, making it possible to imagine the movements and therapy progression in real-time. For remote control, an Augmented Reality (AR) interface is utilized, permitting operators to modify therapy parameters and monitor patient performance parenthetically. In order to ensure personalized treatment, the system continuously adapts the level of difficulty and intensity of the therapy based on real-time feedback. This method is contributive to a highly responsive and effective rehabilitation process, which is perfect for clinical environments as well as home therapy.

3.1. Data Collection (IoT Devices, Wearables, Sensors)

The primary stage of the workflow is to obtain real-time data from diverse IoT devices, wearables, and sensors. The sensors are mounted on the patient's body and on the rehabilitation robot in order to measure important parameters such as joint angles, applied force, muscle activity, and movement patterns. Typically, accelerometers, gyroscopes, and electromyography (EMG) sensors are used to acquire movement, force, and muscle activation information.

Joint Angle Equation: For the measurement of joint angles in real-time under therapy, the sensor data is calculated to determine the angle between two body segments:

$$\theta(m) = \text{atan2}(u_2 - u_1, s_2 - s_1) \tag{1}$$

Where $\theta(m)$ is the joint angle at time m, and (s_1, u_1) and $(s_{2,}u_2)$are the coordinates of the sensors placed on the body.

3.2. Real-Time Data Streaming (Apache Kafka)

Once the data has been collected, it is routed to the system for processing using real-time streaming of data through Apache Kafka. Kafka is a distributed platform for streaming which allows real-time streaming of voluminous amounts of data from the sensors to the other parts of the system with no loss. Kafka ensures that data from different devices, sensors, and wearables is consumed and streamed to the downstream phases of the system without any latency. The throughput performance of Kafka can be represented as follows:

$$G = \frac{K}{C} \tag{2}$$

Where:

- G is the throughput,
- K represents the total count of events (data points),
- C indicates the number of partitions distributed across Kafka brokers.

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3.3. MPC for Therapy Control (Predictive Model)

The robot’s movements are optimized using **Model Predictive Control (MPC)** based on the data received from IoT sensors. It anticipates the future condition of the system (i.e., the robot's movements) and modifies the robot's path to enhance therapy for the patient. MPC operates by addressing an optimization problem at every time step, leveraging the current state to predict future movements.

Objective Function for MPC: In MPC, the optimization problem centers on minimizing the cost function, which usually accounts for state deviations and control effort:

$$\min_{v} \sum_{i=0}^{B} \left(\|s(m+i \mid m) - m_{\text{desired}}\|^2 + \lambda \|v(m+i \mid m)\|^2\right) \tag{3}$$

Where:

- $s(m+i \mid m)$ is the system's predicted state at time $m+i$,
- m_{desired} is the target state (e.g., target joint angle),
- $v(m+i \mid m)$is the control input (e.g., robot actuator movements),
- λ is the control weight used to weigh performance against effort.

The optimization ensures that the movement of the robot is such that it maximizes the efficiency of therapy, optimizes energy expenditure, and eliminates patient injury.

3.4. Digital Twin Visualization

A virtual replica of the physical rehabilitation robot is produced by the Digital Twin. The digital models of the patient and robot are updated by real-time streaming of sensor data, allowing the system to simulate robot movement and the therapy process in a virtual setting. Through this visualisation, one can observe the robot's motion accurately, patient progress, and the operator will be able to get crucial feed back to adapt the session accordingly.

Real-Time Data Synchronization for Digital Twin: The model is updated constantly with real-time sensor data so that there is correct synchronization between the physical robot and the Digital Twin:

$$s_{\text{virtual}}(m) = s_{\text{real}}(m) + \Delta s(m) \tag{4}$$

Where:

- $s_{\text{virtual}}(m)$ represents the state of the Digital Twin at time m,
- $s_{\text{real}}(m)$ is the real state of the robot,
- $\Delta s(m)$ is the instantaneous difference between the robot's actual position and the virtual model's position.

3.5. Augmented Reality Interface for Remote Operation

The rehabilitation robot is remotely operable via the AR interface that provides real-time feedback and patient progress visualizations. It provides low-latency, gesture detection, data overlay, and motion tracking features, allowing intuitive and efficient adjustments to robot motions for therapy management by the operator.

Latency Considerations in AR: The effectiveness of the AR system can be affected by latency, making it essential to reduce delays in both data transmission and display. Latency can be defined as:

$$\text{Latency} = \frac{\text{Time for Data Transfer}}{\text{Number of System Components}} \tag{5}$$

Where it is necessary to maintain a low latency in order to guarantee real-time control of the robot.

3.6. Personalized Upper Limb Therapy

The system tailors upper limb rehabilitation by varying therapy based on real-time data and Digital Twin visualization. For effective therapy, the robot movements are corrected by sensor monitoring and MPC to decrease intensity or alter exercises upon detecting signs of anxiety or fatigue.

Dynamic Therapy Adjustment Equation: The therapy intensity can be altered in real-time, based on the patient's performance data (e.g., muscle fatigue):

$$J_{\text{adjusted}}(m) = J_{\text{current}}(m) - \alpha \times (\text{ Fatigue Level }(m)) \tag{6}$$

Where:

- $J_{\text{adjusted}}(m)$ is the adjusted therapy intensity at time m,
- $J_{\text{current}}(m)$ is the current therapy intensity,
- and α is a parameter that determines the system sensitivity to fatigue levels.

4.Results and discussions

The work was conducted on Python, with the system utilizing real-time data processing and software algorithms for rehabilitation of the upper limb. The system integrates Digital Twin visualization with an Augmented Reality (AR) interface to dynamically adapt therapy based on the patient's performance. Simulations were employed to validate the implementation, demonstrating accurate trajectory tracking and successful therapy adjustments for personalized rehabilitation.

The Physical Action Dataset contains 8 channels of EMG signals from the biceps and triceps of both upper limbs. With Delsys EMG wireless equipment, four subjects (three males, one female) aged between 25 and 30 were data-collected. Ten normal and ten aggressive activities were each performed by every participant, yielding approximately 10,000 recorded samples per subject. This dataset provides useful data on muscle activity that can be employed to study upper limb motion in physical rehabilitation ("EMG Physical Action Dataset," n.d.).

The table contains the primary parameters influencing the system's performance and adjustment of the therapy. It includes the latency, which was found to be 10 milliseconds, ensuring real-time control of the rehabilitation robot. The current therapy intensity is 80 units, and the level of fatigue realized in the patient is 0.5. The adapted therapy intensity is 79.85 units, reflecting a decrease to account for the patient's exhaustion and providing personalized and efficient therapy. These figures demonstrate the system's ability to dynamically adjust and maintain optimal therapy intensity according to real-time data.

Table 1: System Performance and Therapy Adjustment Metrics

Parameter	**Value**
Latency	10 ms
Current Therapy Intensity	80 units
Fatigue Level	0.5
Adjusted Therapy Intensity	79.85 units

The pursuing of Z-axis trajectory is demonstrated in Figure 2, which presents both the desired and actual trajectories. The outcome describes close agreement between the desired and realized trajectories, which signifies that the system successfully controls and adapts the movement of the robot in real-time. This successful tracking deliberates the high effectiveness of the control system in facilitating accurate motion and adaptation, thus assuring consistency and accuracy in rehabilitation therapy under the process.

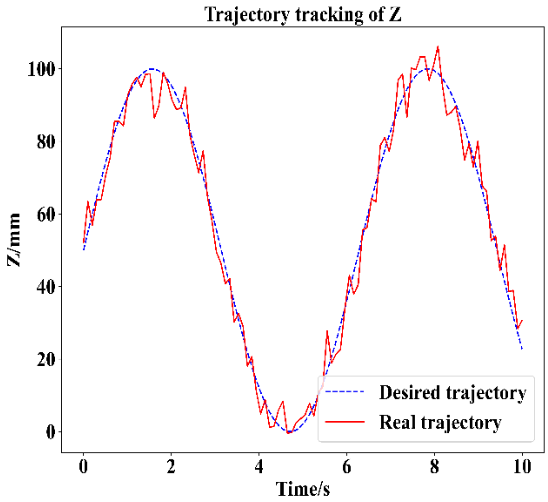

Figure 2: Z-Axis Trajectory Tracking Performance

Figure 3 describes the trajectory tracking error for the X, Y, and Z axes over time. The tracking error for each axis remains within its adequate limit, signifying that the system is managed accurately and diminishes deviation from the desired trajectories. This emphasises the reliability and precision of the system in real-time trajectory tracking.

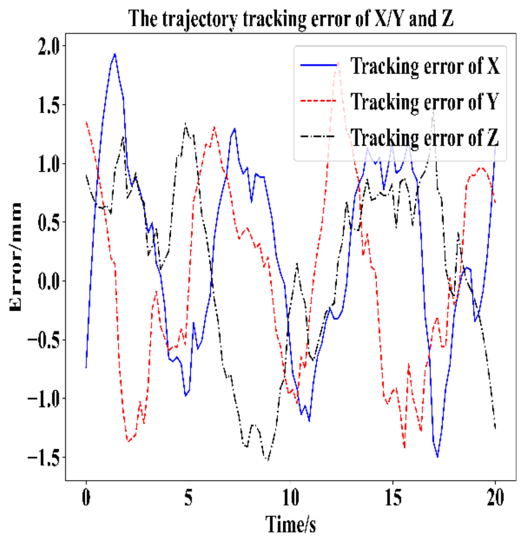

Figure 3: Trajectory Tracking Error of X, Y, Z

The results denote that the system's real-time corrections on the X, Y, and Z axes are able to maintain optimal performance, even under possible disturbances. The small tracking errors in all axes display the robustness of the system in following desired paths, increasing its potential for accurate control in rehabilitation processes.

5.Conclusions

The problem of providing personalized and adaptive rehabilitation therapy for the upper limb through real-time data processing and complicated control methods is addressed in this paper. To assure accurate real-time observation and adjustments to therapy whenever required the system combines Model Predictive Control (MPC), Digital Twin visualization, and Augmented Reality (AR) interfaces. The outcome denote that the system can maintain a low latency of 10 ms and minimize trajectory tracking errors along the X, Y, and Z axes and thus ensure accurate and efficient treatment. Also, adjusting therapy to the patient's fatigue level leads to customized therapy intensities, which maximizes patient comfort and enhances rehabilitation performance. The system's ability to adapt therapy in real time based on patient performance data, thus assuring rehabilitation that is both effective and comfortable. By merging MPC, AR, and Digital Twin technologies, we can improve therapeutic interceptions in rehabilitation systems. This approach ensures both high accuracy and low latency, while also emphasizing the promise of such systems for improving rehabilitation therapies and patient care and recovery.

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